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# Efficient Utilization of Energy in IoT Devices Using Machine Learning Algorithms

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**Abstract:** The expansion of the Internet of Things (IoT) has revolutionized various industries, allowing for the automation of processes, monitoring in real time, and smart decision-making. One of the most significant difficulties confronting IoT devices is energy efficiency, given that many operate on constrained power sources. This study describes the application of ML algorithms in the energy optimization of IoT devices and also analyzes currently available tools for energy efficiency improvement, including predictive modeling, adaptive resource distribution, and energy-aware algorithms. The proposed ML-based adaptive GPS scheduling algorithms show improvement in efficacy in terms of energy consumption and at the same time maintain positional accuracy. This study compares and shows that using the flexible scheduling option is more energy-efficient, especially for users who have diverse patterns of mobility. Furthermore, this study also looks at the potential of ML approaches such as reinforcement learning, supervised learning, and unsupervised learning for predicting device usage, improving energy efficiency, and extending the battery life, which leads to reducing energy consumption while maintaining QoS.

## Introduction

The term the Internet of Things (IoT) depicts the connection of different objects or devices on the internet, for example, sensors, actuators, smart devices etc that collect and exchange data, playing a crucial role in industries like health care, machinery, agriculture, and smart cities (Al-Fuqaha et al., 2015; Jain et al., 2023; Saurabh et al., 2023). They have been extremely successful. Nevertheless, issues abound with their use, one of them being that of energy consumption. Many IoT devices, especially those deployed and designed to be placed in non-manned regions or difficult-to-reach areas, hence the need to use battery-powered devices, which may also not be easy to change (Cheng et al., 2022; Mao et al., 2021). Thus, it is critical to keep these devices running for as long as possible by making smart use of energy or energy-harvesting techniques to improve the efficiency of their energy consumption model (Hisham et al., 2020). Traditional methods for improving the efficiency of energy usage in Internet of Things devices typically rely on predefined rules that are applied to unique scenarios (Sadhukhan et al., 2021; Schmidtke, 2020; Dawn et al., 2023; Gudumian et al., 2024). Traditional approaches, on the other hand, usually have difficulty adapting to the rapidly changing and diverse environments in which IoT devices operate. An intriguing approach to addressing issues with energy management is the crossover of ML integration into IoT networks (Zantalis et al., 2019). Some of the capabilities that are improved with the application of machine learning include the ability for the device to learn usage patterns, provide precise energy forecasts, optimize device operations and adapt to the environment or usage (Cui et al., 2018).

This paper examines the efficiency benefits of employing ML in IoT devices, focusing on their best efficiency-focused ML models and their implementation, as well as contrasted with traditional strategies for managing energy.

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## Review and Gap Analysis

In the past few years, the increasing number of IoT devices and mobile systems has led to significant advancements in scheduling GPS algorithms aimed at minimizing power consumption while maintaining accurate location tracking (Lin et al., 2021; Pallier et al., 2021; Gangadharan et al., 2024). The primary drawback of conventional GPS scheduling algorithms lies in the necessary compromise between energy efficiency and real-time accuracy (Moumen et al., 2023). Earlier systems primarily relied on fixed rule-based methods, which lacked the capability to dynamically adapt to complex scenarios characterized by constant environmental changes, such as transitions in commuting modes or navigation through crowded urban settings. Early techniques, such as duty cycling, have demonstrated effectiveness in minimizing energy consumption by intermittently activating and deactivating the GPS module at specified intervals (Hisham et al., 2020; Pallier et al., 2021). However, these approaches experience latency and decreased precision of location data in scenarios involving high mobility, which limits their applicability for real-world deployment (Johnsana et al., 2024). Several alternative methods, including hybrid location techniques, have been employed to reduce energy consumption. Nevertheless, in extremely dynamic settings marked by frequent changes between walking and driving, these approaches fail to provide sufficient real-time responsiveness (Albraheem et al., 2022; Safa et al., 2021). To address these challenges, multiple studies have been conducted recently, focusing on machine learning-based methods to enhance GPS activation in accordance with user behaviour (Liu et al., 2024; Zhang et al., 2023). Combining GPS in conjunction with alternative low-energy positioning methods like Wi-Fi and Bluetooth has led to the development of hybrid location systems, which further reduce power usage (Aboelsoud et al., 2024; Chen, 2024). Despite various enhancements, the majority of existing solutions depend on the periodic activation of GPS, leading to potential energy inefficiencies in extremely dynamic environments. Other literary works have also been studied. However, while suitable for specific applications, they fail to address the diversity needed to counter modern user movement patterns, which are both dynamic and variable. In his paper, the assertion that ML enhances the energy efficiency of GPS fails to establish connections with edge computing, which significantly restricts its applicability in situations where resources are limited (Zhang and Masoud, 2021; Liu et al., 2024; Chen, 2024). Like this, the research (Amudha and Murali, 2021; Liu et al., 2022; Marahatta et al., 2021a; Yadav et al., 2022) proposed algorithm for optimizing location-based services relies on cloud-based processing and entails significant energy costs associated with data transmission. Several energy-efficient IoT frameworks have been created that combine LPWANs with GPS to enhance battery conservation in constrained devices (Kanakaraja et al., 2022; Mamatnabiyev, 2022). The functionality is primarily contingent upon distinct user actions or fixed schedules, necessitating continuous cloud communication that consumes energy for data transfer overhead (Yadav et al., 2022) and also suffers from latency time as data is not processed in real-time on the edge device (Ma et al., 2023).

The proposed algorithm mitigates these gaps by utilizing in-time sensor data to enhance ML forecasts, while also dynamically managing GPS activation to create a more flexible and energy-aware model. This algorithm is integrated with an edge computing model, enabling local processing of sensor data at minimal energy expenditure to activate GPS and facilitate data transfer (Ma et al., 2023). Consequently, this method provides notable enhancements compared to conventional approaches and facilitates the continuous investigation into energy-efficient IoT systems.

## IoT and Energy Constraints

Some of the major energy constraints for an IoT device are power sources, which are sometimes limited or less opportune to recharge due to its installed location in non-reachable or far-flung areas, power consumption by sensors, processors, communication channels, and the applied algorithm, which is continuously monitoring and processing the data.

### Constraints on Power Sources

The majority of IoT devices integrate practices and mechanisms with limited support, including non-rechargeable batteries or even harvesting methods such as solar energy or kinetic energy (Cheng et al., 2022). As a result of inadequate power supply, devices of this type are manufactured with a low power consumption design. However, there are various reasons that make certain devices inefficient in energy use, for example, the pattern of sending data at intervals that are too short, always on and in a standby mode, and poor design of appliances (Hisham et al., 2020). So, the typical endpoint should be a small, low-power battery-operated or energy-harvesting IoT device with very few or no opportunities to recharge its power source or replace it often. Such remote sensors in smart agriculture (Kulkarni et al., 2024), wildlife or livestock monitoring application (Ilyas and Ahmad, 2020; Mane et al., 2024), face the extreme challenge of being expected to work independently for long periods, often in confined places where energy is scarce. The problem, therefore, is how to reduce the energy consumption of these devices while still offering a certain level of quality of service (QoS) in terms of the accuracy and correctness of information, information turnaround times, and reliable networking (Ding and Wu, 2019; Pandey et al., 2022).

### High Power Consumption in Data Transmission

Energy consumption in IoT devices can be broken down into three major components:

**#Sensing**: Sensory consumption is that associated with utilizing sensor resources toward the acquisition of observable or functional information i.e., the collection of

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environmental or operational data through sensors (Saurabh et al., 2023).

**#Processing**: The computation of the collected data in situ, which includes basic data filtering and decision-making algorithms (Marahatta et al., 2021b; Saurabh et al., 2023).

**#Communication**: The transmission of data between IoT devices and centralized servers or cloud platforms, typically via wireless communication (Mokni et al., 2023).

Among these components, wireless communication often consumes the most amount of energy. Minimizing energy consumption can be achieved by decreasing transmission frequency, enhancing data compression, and optimizing communication protocols. Data transmission generally consumes the most amount of energy in IoT devices (Deng et al., 2021). Wireless communication systems, including Wi-Fi, Bluetooth (Kanakaraja et al., 2022) and Zigbee and LoRa (Cheriyan et al., 2022) exhibit differing power consumption levels contingent upon range and bandwidth. Energy efficiency can be enhanced by minimizing the frequency of data transfer or optimizing the choice of communication protocols according to real-time situations (Hadwen et al., 2017; Noreen et al., 2017).

### Monitoring and Data Processing on a Continuous Basis

Usually, IoT devices such as sensors in smart cities (Cheng et al., 2022; Haroon et al., 2023; Lilhore et al., 2022) or health monitoring devices (Amudha and Murali, 2021; Cheriyan et al., 2022; Hadwen et al., 2017; Safa et al., 2021), function in the monitoring of the environment, and analyze large volumes of data. Unfortunately, continuous activation of sensors as well as processing units consumes a lot of energy. Hence, there is a need for approaches that would cut down unnecessary data processing or forecast inactive durations in order to save battery life.

### Machine Learning for achieving Energy Saving

A machine learning approach could greatly improve the energy consumption of IoT devices. Using the information that has been gathered from the devices, as well as the surrounding environment, ML models are able to control devices and can dynamically adjust device operation in a way that reduces energy consumption (Saranya and Pravin, 2022).

### Supervised Learning Techniques for Power Consumption Minimization

As such, supervised learning utilizes the past information in order to construct a model that will predict how much energy will be used based on the input features such as time of the day, environmental conditions, usage time period, weather, or the type of device that is in use. To achieve energy optimization, some of the effective supervised learning methods (Gui et al., 2024; Zhao et al., 2024) include:

**#Decision Trees:** Simple and interpretable models which are effective in generating an energy management plan.

**#Support Vector Machines (SVM):** It is possible to separate usage modes into either high or low energy states which aid in energy-utilization control and management (Zhao et al., 2024).

**#Artificial Neural Networks (ANN)**: Capable of learning complex patterns in IoT usage and predicting optimal device operation schedules (Farid et al., 2016).

These models can be used to adjust device activity during periods of lower energy demand, switch devices into low-power modes, and predict when battery levels will require recharging.

### Unsupervised Learning for Pattern Recognition

Models for unsupervised learning pattern recognition do not require labelled training sets. These algorithms can also aid in detecting energy consumption anomalies or finding out some aspects of usage of devices that were previously unknown (Naeem et al., 2023; Talaei Khoei and Kaabouch, 2023) for example,

**#Clustering algorithms:** These are used to analyze similar device operations to create energy profiles for each cluster. For example, devices with common usage characteristics can be managed together to save up on consumed energy (Talaei Khoei and Kaabouch, 2023).

**#Dimensionality reduction:** These are primarily implemented through techniques like Principal Component Analysis, which can reduce the complexity of IoT data, enabling more efficient decision-making processes without hindering performance (Talaei Khoei and Kaabouch, 2023).

### Reinforcement Learning for Dynamic Energy Management

Reinforcement Learning (RL) is a very promising solution to the energy management problem owing to its efficiency in real-time and uncertain domains. In reinforcement learning, the agent is embedded in an environment and allowed to carry out some actions, which are rewarded or punished (Meng et al., 2024; Wang et al., 2023). Some notable applications of RL in Optimization of energy in IoT include:

**#Dynamic power management:** These policies and algorithms will, via RL, adjust the various states of the IoT devices, e.g., deep sleep mode, active mode, and so on, in consideration of the real-time operational and environmental factors.

**#Energy harvesting systems:** In energy-harvesting IoT systems, RL can be employed to optimize energy storage and consumption, thereby ensuring that the harvested energy is utilized efficiently across devices.

### Predictive Models for Energy Forecasting

In situations where IoT devices must anticipate future energy consumption and modify their behaviour accordingly, predictive models are indispensable. Machine learning models such as Long Short-Term Memory (LSTM) networks and regression algorithms can forecast energy usage patterns based on historical data,

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enabling devices to switch to energy-saving modes during periods of low demand (da Silva and Meneses, 2023; Suseendran et al., 2022).

### Energy-Aware Routing Protocols

Machine learning can also enhance energy efficiency through the design of energy-aware routing protocols in multi-hop IoT networks). These protocols can learn the energy levels of various devices in the network and adapt routing decisions to ensure that data packets are sent via the most energy-efficient path, thereby prolonging network lifetime (Samadi et al., 2023).

## Use of IoT Devices in Day-to-day life

IoT devices incorporated in a smart home such as smart thermostats, lighting systems, and other appliances typically produce data that can help in optimizing energy consumption within households (Sadhukhan et al., 2021; Saurabh et al., 2023). Such devices incorporate ML models and can tell the user's behaviour, such as whether occupants are at home, and use this information to manage energy progressively. Houses with smart ML systems have reported improvements in energy efficiency while in use during peak hours (Haroon et al., 2023). For instance, reinforcement learning algorithms are capable of learning the user's needs and automatically adjusting lighting and other systems to the minimum level when the house is unoccupied. Within the framework of smart agriculture, specific sensors are used to analyze environmental conditions like moisture and temperature for improved irrigation and farming procedures (Kulkarni et al., 2024). Weather forecasting using machine learning is useful for reducing energy consumption in irrigation systems by rescheduling irrigation time depending on the weather (Ilyas and Ahmad, 2020). This means one does not need to have the sensors constantly monitored and the collected data transmitted. In industrial IoT (IIoT), energy efficiency is critical for managing vast sensor networks, machinery, and control systems (Saurabh et al., 2023). In this sector, predictive maintenance is a key application of ML for energy efficiency. ML models can analyze sensor data from machinery to predict equipment failures before they occur. This allows for timely maintenance, reducing the need for energy-intensive monitoring systems and avoiding downtime that could lead to energy inefficiencies (Mao et al., 2021; Mukherjee et al., 2020). Also, RL-based solutions have been used to optimize the energy consumption of manufacturing processes dynamically.

## Proposed Machine Learning Algorithm for Adaptive GPS Scheduling in IoT Devices

GPS modules are of great importance in IoT applications like intelligent mobility and ecological surveillance. Nonetheless, continuous GPS use is power hungry, which is a critical drawback especially for devices with limited power resources. The novel adaptive GPS scheduling ML algorithm taken in this manuscript describes an optimal way of scheduling the GPS devices to manage the consumption of power and the positional accuracy of the device. This rational algorithm utilizes past and real-time information methodically and, with intelligence, develops durations between GPS activation based on the user's movements and environmental conditions.

### Context-based problem identification

Many IoT applications demand accurate positional data. Nonetheless, simply switching on and off the GPS Module at regular intervals once in a while wastes battery when the device is stationary or is moving in a range of space. There is a need for a more sophisticated, adaptive scheduling algorithm to determine when and how often the GPS should be activated, depending on the context.

### Dataset Used: Geolife GPS Trajectory Dataset from Microsoft Research

For implementation and verification of the proposed ML algorithm on adaptive GPS scheduling, several public datasets related to GPS trajectories, movement trends, and data collected by sensors, etc. are available. In this manuscript the Geolife GPS Trajectory Dataset from Microsoft Research (Zheng et al., 2023) is used as the primary dataset to fit and evaluate mobility prediction models because of the following features:

**#Rich GPS Data**: This dataset contains 17,621 trajectories collected from 182 users over a period of five years, which means there is abundant information on GPS. Data such as latitude, longitude, altitude, timestamps, and type of transportation which can be walking, driving or biking, etc. are all contained in this dataset which makes it easier to predict mobility.

**#Variety of Mobility Scenarios**: It includes people using different modes of transport like walking, driving, biking and using public transport. This diversity is important for training the movement trends to differentiate between no movement, moderate and high-speed movements.

**#Time of Day Context**: The time of day not only helps group people into various cycles but also helps the model predict what type of movements are most likely to be repeated, such as movement to and from work on a daily basis, which is also helpful in optimizing GPS scheduling for the model.

**#Real-World Use Case**: The dataset works well for practical purposes like smart transportation or wearable IoT devices, in cases when precise GPS scheduling is necessary to achieve power savings.

Below are some commonly used datasets available across various dataset provider websites that can be used to verify this algorithm:

**#Dublin Bus GPS Data:** This dataset contains the real-time GPS positions of buses in Dublin city, Ireland. It contains coordinates, timestamp, and other contextual information like bus route and the existing traffic conditions (*Dublin Bus GPS Sample Data (Insight Project) From DCC - Dublin Bus GPS Data - data.smartdublin.ie*, n.d.). This is helpful for evaluation of the algorithm in a public transportation domain, where

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movement patterns (such as bus stops and fixed routes) can be predicted and altered for energy-efficient GPS scheduling.

**#Brightkite Social Network Data:** This dataset contains check-ins from the Brightkite location-based social network; in this, the user's GPS coordinates and timestamps are provided, but the dataset is sparser compared to continuous GPS trajectory data (*SNAP: Network Datasets: Brightkite*, n.d.). This dataset can be used to analyze user movement over longer time intervals and determine optimal GPS activation periods for low-frequency movement.

### Dataset utilization method:

**#Mobility Prediction Model**: Using Geolife dataset, the historical GPS coordinates and derived features like time of day, speed and other sensor data are used to train a ML model by splitting the data into training and testing sets to train a classifier for Random Forest, that predicts the device mobility states like stationary, walking or driving.

**#Reinforcement Learning for Energy Scheduling**: Based on the mobility state predicted by the model, the GPS activation interval is dynamically adjusted to reduce energy consumption while maintaining sufficient positional accuracy.

**#Evaluation**: Test the proposed adaptive GPS scheduling algorithm with two baselines Fixed Interval Scheduling and Random Activation to compare energy consumption and positional accuracy across varying scenarios like pedestrian vs. vehicle-based movements.

### Algorithm Overview

Here in this manuscript, a two-part ML method for adaptive GPS scheduling-the development of a model to forecast movement and a scheduler to optimize power consumption.

**#Movement Forecast Model:** Using historical GPS data and other sensor inputs, this model aims to forecast the device's future movement trend.

**#Power Optimization Scheduler:** This scheduler dynamically modifies the GPS activation intervals to strike a compromise between energy efficiency and the necessary positional accuracy, taking into account the movement forecasts.

A variety of contextual factors, such as location, velocity, time of day, and whether the user is stationary, walking, or driving, are used to train the model through supervised learning on historical data.

### Proposed Algorithm Details

The proposed GPS scheduling algorithm will work in the sequence as presented in figure 1 and elaborated for easy understanding.

After powering up an IoT device, its sensors will begin collecting data, which will then be sent to the processor for processing. The processor will then make use of the data. The machine learning algorithm then steps in to forecast user behaviour, adjusting the GPS activation schedule, data transmissions, and energy consumption monitoring accordingly.

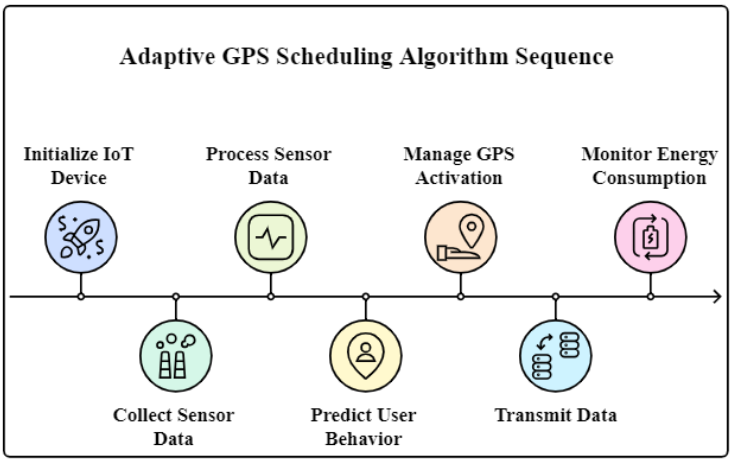


**Figure 1. Activity Sequence of Algorithm.**

### Input Features

#The device's prior locations.

#Velocity is derived from successive GPS coordinates.

#Positioning the Device

#Movement and velocity of the gadget.

**Movement Forecast Model (part 1):** The dataset is used to train a machine learning model that uses speed and, possibly, latitude and longitude, to forecast the mobility status. Here are the potential states:

#No movement

#Moderate movement like strolling

#High movement like driving

For each given time t, let X(t) represent the set of input features, which may include past GPS coordinates and sensor data. The model's end purpose is to generate forecasts:

$P(\text{movement state}_{t+1}|X(t))$

When given data like speed, latitude, and longitude, the Random Forest classifier was able to predict the mobility statuses with a perfect score. Because of this, we may conclude that the model has successfully learned all of the dataset's patterns. If this forecast pans out, we'll know exactly when to turn off or lower the GPS's frequency to save power, whether we're standing still or going for a walk.

**Power Optimization Scheduler (part 2):** After a precise prediction of the user's movement status has been made, adaptive GPS scheduling can begin, with the RL model adjusting the activation intervals of the GPS system according to the projected movement status:

**#No movement**: Reducing the GPS frequency can help save energy.

**#Moderate movement**: Moderate GPS frequency.

**#High movement**: A high frequency (to improve the precision of location).

While keeping its position precisely recorded, this RL agent will use as little energy as possible. The system rewards energy savings, while a severe positional mistake is penalized.

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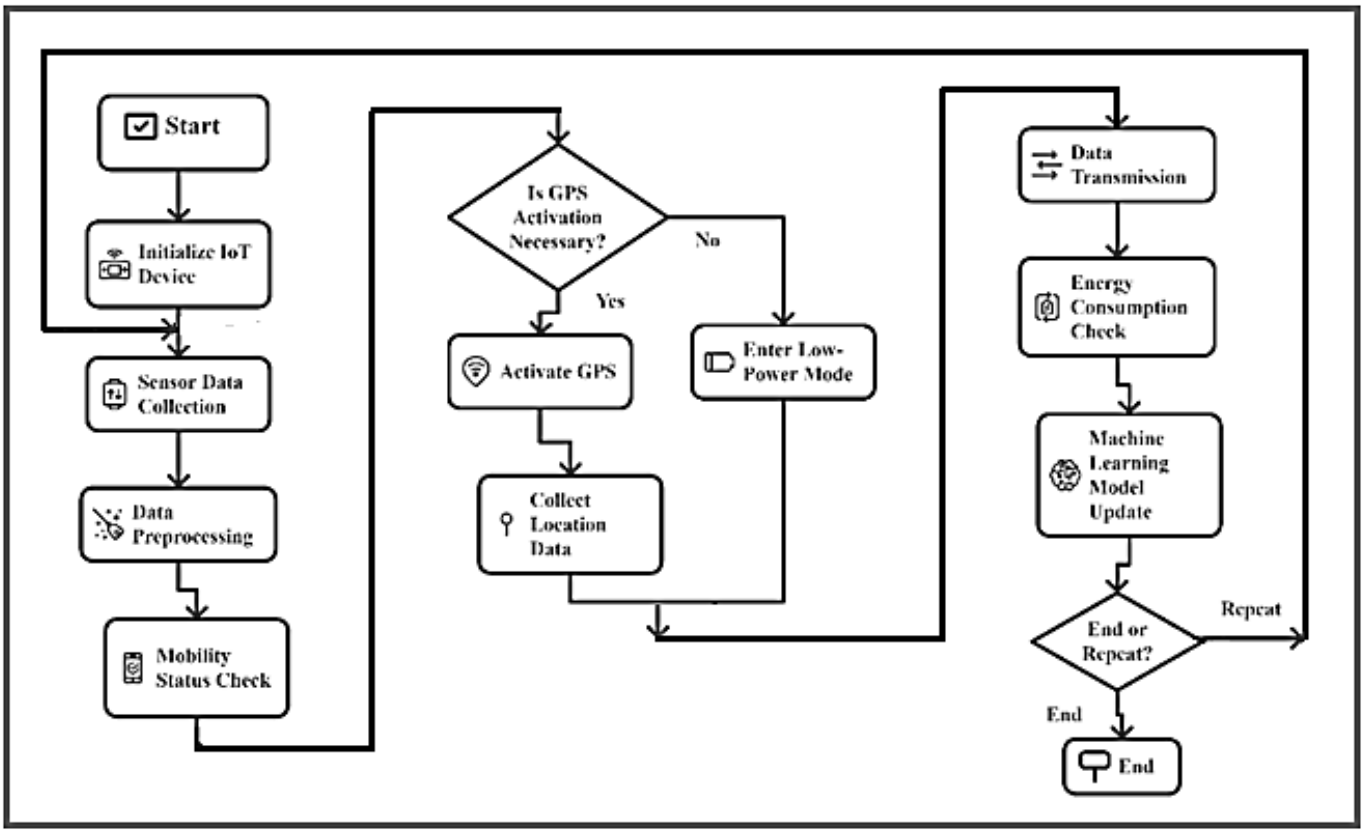


**Figure 2. Flowchart for Adaptive GPS Scheduling Algorithm.**

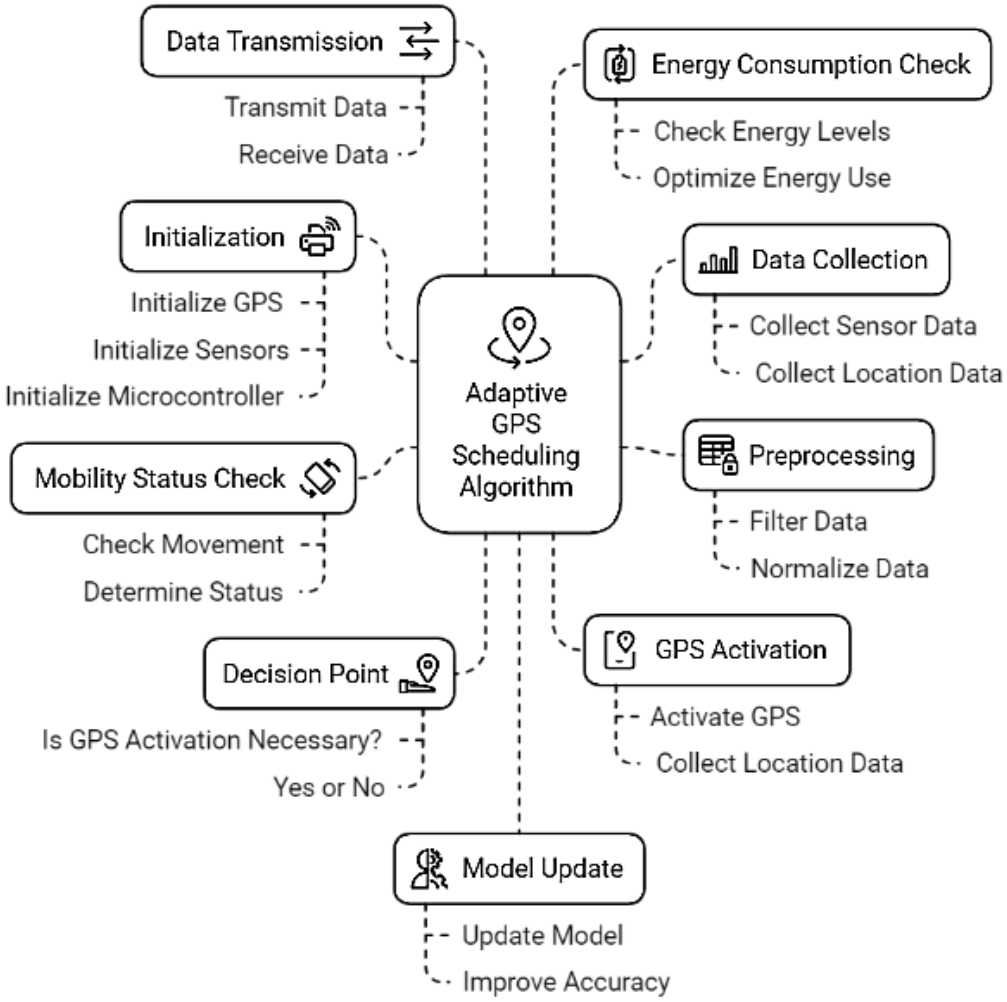


**Figure 3. Features of the proposed Adaptive MLA.**

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The adaptive GPS scheduling algorithm uses the dataset and the ML model through Python programming. The whole process includes the following steps:

**#Data Preparation**: Load the dataset and prepare features and target labels. In this state, once the dataset is loaded, ML model prepares the features and 'timestamp', 'latitude', 'longitude', 'speed', 'mobility_state' labels.

**#Model Training**: Train a Random Forest classifier to predict mobility states. In this step, a random forest classifier model is initialized, trained on the data and the trained model is then applied to predict the mobility state on the test set.

**#GPS Scheduling**: Apply the predicted mobility states to determine GPS activation intervals. In this step, GPS scheduling intervals (in seconds) based on the mobility state are defined.

**#Results**: Display the results with timestamps, predicted mobility states, and GPS intervals. This final step will now display the results as per the label defined in step 1

result_columns = ['timestamp', 'latitude', 'longitude', 'speed', 'predicted_mobility_state', 'gps_interval']

print(all_test_cases[result_columns].head(50)) # Display the first 50 rows of results in table 1

**Table 1. Test Cases.**

| Timestamp (date and time) | Latitude | Longitude | Speed (km/h) | Mobility state | | Timestamp (date and time) | Latitude | Longitude | Speed (km/h) | Mobility state |
|---|---|---|---|---|---|---|---|---|---|---|
| 01-10-2023 08:00 | 39.984 | 116.318 | 0 | Stationary | | 01-10-2023 08:25 | 39.984 | 116.318 | 0 | Stationary |
| 01-10-2023 08:01 | 39.985 | 116.319 | 5 | Walking | | 01-10-2023 08:26 | 39.985 | 116.319 | 5 | Walking |
| 01-10-2023 08:02 | 39.986 | 116.32 | 15 | Cycling | | 01-10-2023 08:27 | 39.986 | 116.32 | 15 | Cycling |
| 01-10-2023 08:03 | 39.987 | 116.321 | 30 | Driving | | 01-10-2023 08:28 | 39.987 | 116.321 | 30 | Driving |
| 01-10-2023 08:04 | 39.988 | 116.322 | 60 | Driving | | 01-10-2023 08:29 | 39.988 | 116.322 | 60 | Driving |
| 01-10-2024 08:05 | 39.984 | 116.318 | 0 | Stationary | | 01-10-2023 08:30 | 39.984 | 116.318 | 0 | Stationary |
| 01-10-2023 08:06 | 39.985 | 116.319 | 5 | Walking | | 01-10-2023 08:31 | 39.985 | 116.319 | 5 | Walking |
| 01-10-2023 08:07 | 39.986 | 116.32 | 15 | Cycling | | 01-10-2023 08:32 | 39.986 | 116.32 | 15 | Cycling |
| 01-10-2023 08:08 | 39.987 | 116.321 | 30 | Driving | | 01-10-2023 08:33 | 39.987 | 116.321 | 30 | Driving |
| 01-10-2023 08:09 | 39.988 | 116.322 | 60 | Driving | | 01-10-2023 08:34 | 39.988 | 116.322 | 60 | Driving |
| 01-10-2023 08:10 | 39.984 | 116.318 | 0 | Stationary | | 01-10-2023 08:35 | 39.984 | 116.318 | 0 | Stationary |
| 01-10-2023 08:11 | 39.985 | 116.319 | 5 | Walking | | 01-10-2023 08:36 | 39.985 | 116.319 | 5 | Walking |
| 01-10-2023 08:12 | 39.986 | 116.32 | 15 | Cycling | | 01-10-2023 08:37 | 39.986 | 116.32 | 15 | Cycling |
| 01-10-2023 08:13 | 39.987 | 116.321 | 30 | Driving | | 01-10-2023 08:38 | 39.987 | 116.321 | 30 | Driving |
| 01-10-2023 08:14 | 39.988 | 116.322 | 60 | Driving | | 01-10-2023 08:39 | 39.988 | 116.322 | 60 | Driving |
| 01-10-2023 08:15 | 39.984 | 116.318 | 0 | Stationary | | 01-10-2023 08:40 | 39.984 | 116.318 | 0 | Stationary |
| 01-10-2023 08:16 | 39.985 | 116.319 | 5 | Walking | | 01-10-2023 08:41 | 39.985 | 116.319 | 5 | Walking |
| 01-10-2023 08:17 | 39.986 | 116.32 | 15 | Cycling | | 01-10-2023 08:42 | 39.986 | 116.32 | 15 | Cycling |
| 01-10-2023 08:18 | 39.987 | 116.321 | 30 | Driving | | 01-10-2023 08:43 | 39.987 | 116.321 | 30 | Driving |
| 01-10-2023 08:19 | 39.988 | 116.322 | 60 | Driving | | 01-10-2023 08:44 | 39.988 | 116.322 | 60 | Driving |
| 01-10-2023 08:20 | 39.984 | 116.318 | 0 | Stationary | | 01-10-2023 08:45 | 39.984 | 116.318 | 0 | Stationary |
| 01-10-2023 08:21 | 39.985 | 116.319 | 5 | Walking | | 01-10-2023 08:46 | 39.985 | 116.319 | 5 | Walking |
| 01-10-2023 08:22 | 39.986 | 116.32 | 15 | Cycling | | 01-10-2023 08:47 | 39.986 | 116.32 | 15 | Cycling |
| 01-10-2023 08:23 | 39.987 | 116.321 | 30 | Driving | | 01-10-2023 08:48 | 39.987 | 116.321 | 30 | Driving |
| 01-10-2023 08:24 | 39.988 | 116.322 | 60 | Driving | | 01-10-2023 08:49 | 39.988 | 116.322 | 60 | Driving |

The flowchart given in Figure 2 outlines the flow of the adaptive GPS scheduling algorithm, which intelligently controls GPS usage to maximize energy efficiency in IoT devices or mobile systems. The key steps are collecting real-time data through sensors like accelerometer and gyroscope, analyze the collected data with ML model that predicts the user's mobility state, here it takes State-Based Decision, like If the user is predicted to be driving or cycling, the GPS is activated frequently to get location data or If the user is stationary or walking, the GPS is either deactivated or activated less frequently (based on a timer) ensuring energy savings when possible and once the data is fetched and the GPS is deactivated, the system goes back to monitoring the sensor data for new inputs. This ensures that GPS is only used, when necessary, based on real-time predictions, leading to more energy-efficient location tracking. The one view of proposed adaptive MLA with all features are in presented figure 3 below.

## Simulation

In Simulation, algorithm is evaluated on simulated environment using past GPS traces from real-world datasets. The dataset includes location information, speed, and patterns of travel for both people and vehicle. Using the Geolife GPS Trajectory Dataset, the algorithm can be tested in different contexts like stationary periods, slow pedestrian movement, and high-speed vehicular scenarios. This allows for a robust evaluation of energy savings and positional accuracy across diverse mobility patterns.

Here are 50 test cases from a Geolife GPS trajectory dataset as shown in table 1:

Using varying time intervals and GPS coordinates, these test cases mimic a range of movement patterns, including standing, walking, cycling, and driving. The

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adaptive GPS scheduling algorithm's performance can be assessed using these.

```
# Extending the test cases with an additional 150 rows for different dates
additional_data = {
    'timestamp': pd.date_range(start='2024-10-02 08:00:00', periods=150, freq='T'),
    'latitude': [39.984, 39.985, 39.986, 39.987, 39.988] * 30,  # Same pattern of Latitudes
    'longitude': [116.318, 116.319, 116.320, 116.321, 116.322] * 30,  # Same pattern of Longitudes
    'speed': [0, 5, 15, 30, 60] * 30,  # Similar pattern of speeds
    'mobility_state': ['stationary', 'walking', 'cycling', 'driving', 'driving'] * 30  # Mobility states
}
# Creating a DataFrame for the additional data
additional_test_cases = pd.DataFrame(additional_data)
# Combining the original 50 test cases with the new 150 cases
all_test_cases = pd.concat([test_cases, additional_test_cases], ignore_index=True)
# Display the first 200 test cases
all_test_cases.head(200)
```

This dataset will be used to test the adaptive GPS scheduling technique.

## Outcomes and Discussion

In a conventional GPS algorithm, the GPS is constantly activated regardless of the user's mobility state, so the energy consumption is continuous, leading to potential waste during periods of low movement. While in Adaptive GPS Scheduling Algorithm can be altered on case-to-case basis, like where high priority and intensive location data is required along with energy optimization like for any high profile person, intensive medical emergency cases, disaster relief program, in such cases the prediction and activation algorithm can be altered in different ways which saves more than 16% energy in comparison to traditional approach while for general usage like daily commute from one place to another with in a city, inter-city or state movement, or non-critical and emergency movement, the prediction and GPS activation algorithm is altered in such a way which can save around 47% energy in comparison to traditional approach.

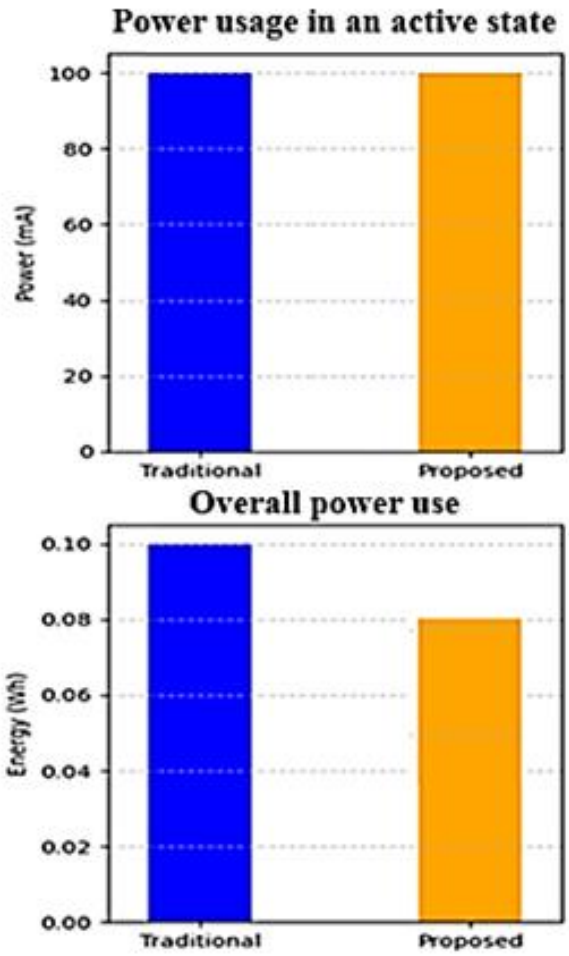
## Comparative Analysis

Several considerations and computations are required to evaluate the adaptive GPS scheduling algorithm's energy efficiency. An evaluation of a one-hour behavioural pattern that consists of thirty min. of drive, twenty min. of walking, and ten min. of stationary. In comparison to the conventional model, which is displayed in table 2, this assessment looks at how well the suggested model works in real time.

The comparative analysis between the performance of proposed algorithm w.r.t conventional algorithm for one hour, in terms of power usage in active state, one hour worth of activity, overall power use, power savings, movement adaptation, and location accuracy are provided below in table 2 that demonstrate the effectiveness of the proposed algorithm and illustrated in figure 4.

**Table 2. Experimental Result and Comparison.**

| Aspect | Conventional algorithm | Proposed Algorithm |
|---|---|---|
| Power usage in an active state | 100 mA | 100 mA |
| One hour's worth of activity | 1 hour | 0.833 hr |
| Overall power use | 0.1 Wh | 0.0833 Wh |
| Power savings | None | consumed 16.67% less power |
| Movement adaptation | None | Modifies itself according on the current state of motion |
| Location accuracy | Constant | High during movement, less when no movement |



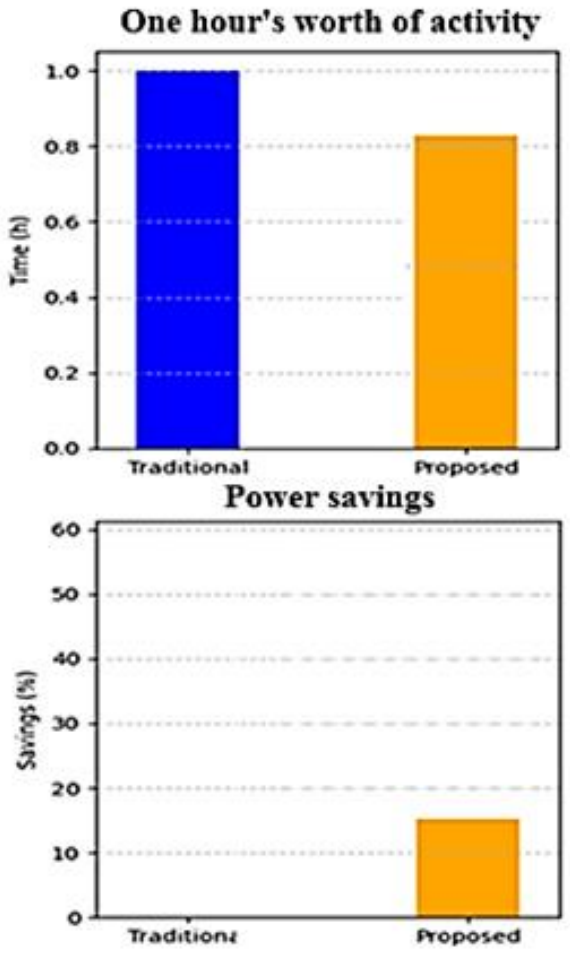



**Figure 4. Evaluation for distinct characteristics.**

## Conclusion

The proposed ML-based adaptive GPS scheduling algorithms show improvement in efficacy in terms of energy consumption and at the same time maintain positional accuracy. The combined movement forecast stage and energy optimization scheduler working in a combination presents a system that alters with the movement of IoT devices. The adaptive GPS scheduling algorithm when compared to the conventional approach demonstrates a 16.67% reduction in energy consumption, primarily due to its ability to adapt to movement states and diminish GPS activation during motionless periods. This comparison shows that using the adaptive scheduling method is more energy-efficient, especially for users with varying movement patterns, providing both energy savings and maintaining accuracy during critical movement periods. Energy efficiency is a critical challenge for IoT devices, especially those operating in energy-constrained environments. By making energy management more flexible, predictive, and autonomous, ML provides a viable alternative. In order to reduce power consumption without sacrificing quality of service, methods like clustering, reinforcement learning, and predictive modeling might be quite useful. Looking into the fact that the scale and complexity of IoT networks are on the rise, the need to employ machine learning to optimize energy utilization in IoT networks will only get stronger.

## Conflict of the interest

None

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## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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